THE USE OF INTERNAL RATING MODELS IN MANAGING THE RISKS RELATED TO THE EXPOSURES OF NON-BANKING FINANCIAL INSTITUTIONS

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Abstract
Although there is no express requirement in the regulations of the National Bank of Romania, the design, the implementation and the use of rating systems in the management of risks related to exposures of non-banking financial institutions (NFIs) on the basis of good banking practice, is a valuable and indispensable in the efficient administration of risks, especially in the current crisis. In this framework, this study describes the synthetic process of reviewing the *scoring* system used by IFN. The mechanism for evaluation of *scoring* system performance combines the indicators of discrimination power with econometric results of studying the functional relationship between risk variables integrated in the model and the credit status (default/ reimbursement) based on *logit* model. The empirical analysis provides clear evidences that while the discriminatory power related to qualitative component (reputational *scoring*) respects the requirements of a good ex-ante identification of non reimbursement cases, the power of discrimination of quantitative *scoring* is only marginally superior to a random model. The added value of the study is completed by highlighting the importance of technical conditions of financing facility for anticipating events of non reimbursement. At the same time, the study tries to highlight the importance of scientific calibration of such a *scoring* system to perform effectively in the early detection of cases of default.

Keywords: non-banking financial institutions, credit risk, *scoring* model, univariate analysis, multivariate analysis, ROC curve, discriminating power.

JEL classification: G23,G32

Introduction

The literature set apart several internal models for key risks evaluation, both theoretical, and particularly with practical applicability. Major players in the banking market developed models that became reference benchmarks at both empiric and academic levels. The most reputed models are Portfolio Manager and Credit Metrics, prevalently used in economies with a developed capital market. The Portfolio Manager model was developed by Moody's

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and capitalizes Merton's idea (1958) of treating equity as an option on the company's assets. In this way, a company's creditworthiness may be assessed comparing its market value to its debts level. We encounter the same conditionality in the case of the Credit Metrics model elaborated by J.P. Morgan, based on which the Value-at-Risk concept was developed at the same time (Jorion, 2001). Value-at-Risk methodology was subsequently accepted as a standard in the financial industry, under the name of Risk Metrics.

Unlike credit institutions, non-banking financial institutions, as Romanian legislation defines them, are subject to BASEL II supervisory regulations only at macro-level, respectively from the perspective of the 2nd and 3rd Pillars, regarding the supervision of capital adequacy and market discipline. The adequacy of NFIs' capitals shall be made from the perspective of fixed risk quotas set by the supervision authority. Such quotas are not subject to review depending on the dynamics of the economic cycle, business sector or financial performance of the counterparty, and shall apply in a uniform manner to those categories of clients or of debtors related to the gross exposure thresholds set by the supervision authority.

Fundamental changes in the financial markets, increasing globalization and deregulation, and corporate restructuring had a significant impact on the magnitude and nature of risks facing the financial industry (Dima, 2010). In the context of the current financial crisis, Mihm and Roubini (2010) consider that the incapacity of both regulation and supervision to keep up with financial innovation also played a role in its initiation. 'Shadow' banks, as Roubini (2008)[1], called them, are financial institutions, which look like banks, act like banks, lend and borrow like banks and – perhaps surprisingly – are not regulated like banks. However, some authors (Oprescu and Damtoft, 2009) believes that excessive regulation in the name of financial stability can destroy competition and considers as being important to find that balance to a level of market regulation to ensure the stability of the financial system and a level of competition that does not affect the free market mechanisms. The issues that generated the crisis remain standing and one of them – less regulation or even a lack of regulation of financial institutions other than banks sector – may represent the cause for commencement of next financial crisis. Laeven and Valencia (2008), quoted by Dardac and Giba (2010), demonstrate through empirical analyses that exception from prudent regulations for the financial sector are fiscally costly and do not accelerate the economic recovery process, while in Romania this process of recovery will be lasting and more difficult than in other EU countries (Albu and Dinu, 2009). This is the reason why, in our opinion, the investigation of the methods, used by banks at the level of NFIs, to implement credit risk management techniques is part of the efforts made by the academic environment to explain and anticipate future financial crises. On the other hand, the role of central bank regarding supervision of risks management should also increase, in agreement to the new European supervision institutions, in order to anticipate and prevent systemic crises as the one, which aspects and magnitude we are nowadays experiencing (Chiriac and Dardac, 2010).

[1] After he had launched the expression at a Fed Conference in Jackson Hole, in 2007, Paul McCulley published it in an info bulletin for Global Central Bank Focus, PIMCO 'The Shadow Banking System and Hyman Minsky's Economic Journey'. Roubini took the expression over and used it in the most of the works on the banking-financial crisis.

NFI field in Romania is new; it has its roots in BNR legislation in 2006-2007 when the Central Bank decided to integrate these institutions in the financial industry that regulates and supervises. Scientific research in this area is new and of banking inspiration. The major difference between managing banking and that of the NFI specificity resides in the latter. The novelty of our research is given by the conclusion of the study: the use of specific *scoring* systems for the banking system in credit risk management in the NFIs is an essential key for management performance of credit risk faced by these institutions. The application of the quantitative evaluation criteria on the discriminating power considered the elaboration, testing and validation of the *scoring* model designed for NFIs, at the level of *finance lease*.

1. Methodological aspects

Evaluation mechanism of NFI's performance internal *scoring* system that was analyzed, combines indicators of discrimination power with the econometric results of studying the functional relationship between risk variables integrated in the model and credit status (default / reimbursement) based on *logit* model.

1.1 The analyzed internal scoring system

NFI, subject to research in this study, calculates a *scoring* of beneficiaries of finance lease, by combining a score of given quantitative elements (*SFQant)* and qualitative elements (*SFQal*).

$$SFTotal = SFQant + SFQal \qquad (1)$$

In the *scoring* model we have used the same notations as in the case of credit institutions for customers and potential customers according to multivariate analysis. The maximum score obtainable for general *scoring* function (*SFTotal*) is 160 points (table no. 1) divided into classes of credit risk.

Table no. 1: Final general *scoring* based on risk categories

Client type depending on risk category	General *scoring* against risk classes
A	From 131 to 160 points
B	From 101 to 130 points
C	From 71 to 100 points
D	From 41 to 70 points
E	From 0 to 40 points

1.1.1 The scoring system based on quantitative information

Scoring function of quantitative information (*SFQant)* is defined by two factors, namely the intermediate score of counterparty risk based on financial performance *(SiRC)* and the final score given by the technical risk (*SRT*).

$$SFQant = SiRC + SRT \qquad (2)$$

NFI gives maximum 70 points for the component related to financial performance, and namely, maximum 30 points for the component related to the technical risk. Financial performance is evaluated based on indicators that express the characteristics of liquidity, solvency, profitability and efficiency of the credit borrower (table no. 2). Its analysis does not have a purely static character, the financial score is calculated based on indicators in the last two reporting periods.

Table no. 2: *Scoring* system of financial performance

Financial *Scoring*	CLASS E		CLASS D		CLASS C		CLASS B		CLASS A	
	Level	Score	Level	Score	Level	Score	Level	Score	Level	Score
Current Liquidity (%)	<50	2	<70	4	<=90	6	<100	8	>=100	10
Indebtedness (%)	<100	2	<95	4	<85	6	<75	8	<65	10
Solvency ratio (%)	<100	2	<80	4	<70	6	<60	8	<50	10
Rate for. debt (%)	<100	2	<120	4	<140	6	<160	8	>=160	10
ROA	<5	2	<7	4	<9	6	<11	8	>=11	10
Commercial rentab. (%)	<10	2	<20	4	<25	6	<30	8	>=30	10
Net cash	<0.1	2	<0.5	4	<0.7	6	<1	8	>=1	10
Total	**14**		**28**		**42**		**56**		**70**	

Technical risk is based on uncertainty about the residual value, particularly relevant after the counterparty ceases to repay. In this case, NFI must recover the object of lease property (movable or immovable) and in the next stage, to exploit it.

Depending on the market of each asset (real estate, used car market - second hand) exists the recovery risk lower than the debt that the counterparty has to pay to NFI. Thus, in technical risk calculation are taken into account the factors that can influence the price for brand and model of vehicle required to finance – in case of automobile assets: type of vehicle, moral wear level, destination, network maintenance, and if they fall within the standard requirements for that model (of great importance is the advance level and funding period) as shown in table no. 3. The importance of the technical risk lies in the fundamental difference between credit type financing and leasing type, meaning that if the latter the property remain to the lessor (the NFI) until full payment of obligations. Therefore, from the perspective of the lessor, at any time, the revalue of the property's value subject to the lease obligations exceed the amount remaining to be paid by the lessee (while the debtor gives up the contract).

Table no. 3: *Scoring* system of technical risk

Criteria	Variants/Score		
Vehicle type	**car**	**van**	**motorcycle/ ATV/others**
	5	3	2
Physical wear level	new	0-3 years/ in guarantee	over 3 years
	5	3	1
Moral wear level	new model *(1 year max)*	average age model *(4 years max)*	old model(over 4 years)
	3	2	1
Specialization degree	absence *(standard)*	medium *(minimal changes)*	high *(radically adapted)*
	5	3	1
Destination	passengers transportation	goods transport	school, taxi, security protection, courier
	5	3	1
Network service	very developed network	average developed network	underdeveloped network
	3	2	1
Standard advance /funding period	fits	does not fit	
	4	2	

1.1.2 Development of the scoring function with qualitative information

Qualitative information are often more important than quantity. Financial performance and technical performance of the property subject of the leasing contract are not enough to detect possible fraud in circumstances where, for example, existing shareholders have recently taken a company with excellent financial results and want to use it as a front for a scam. As a result, reputational elements should be included in the calculation methodology of *scoring* by qualitative analysis. Although the BNR regulations require these checks for any reports to the National Office for Preventing and Combating Money Laundering, in our opinion, they are binding on the customer knowing that the institution wishes to enter into a relationship over the coming years. Quality elements taken into account to determine the *scoring* function are related to the legal status (if the company operates and is not insolvent and that litigation is involved - BPI behavior and conduct in court), the behavior related to payment (as has honor payment obligations - CIP conduct, CRB behavior and conduct of taxes payment) [2] and those related to the reliability of the company and its management organs (table no. 4). The score for financial discipline when using payment instruments may be zero due to the existence of three payment incidents recorded by the head office of event payments, that two promissory notes and a check given by the applicant without coverage. The analyst will investigate these incidents and will present details of these events to the committee of loan approval. At the same time, the analyst must relate the importance of these elements with their age and their materiality for example related to the (turnover).

Table no. 4: Calculation of qualitative information *scoring*

Behavior	Description	Possible *scoring*	Calculation formula
CIP Behavior	Event payments	0-10	Max(0,Round((1-"The amount refused to pay "/Financed value*10,0))
CRB Behavior	Other unpaid loans	Depending on the delay	Max 15 days=10; 16-30 days =7,31-60 days=4,61-90 days=2; over 90 days=0
State Behavior	Payment of taxes	0-10	Max (0,10*(1-Debt to the State Budget/Average Turnover)
Court Behavior	Trials sin court	10,5,0	Based on the gravity of the processes with which the client appears on Court's portal
Google Behavior	Reputation based on the articles written on the Internet	10,5,0	Based on the client's reputation and in accordance with the articles published on the Internet
BPI Behavior	Insolvency	10 Non financed	Registration to BPI means non financed

1.2 Evaluation mechanism for scoring system performance

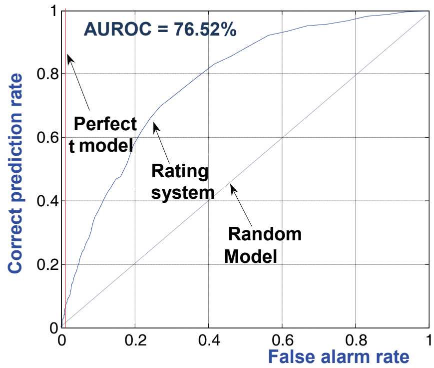
Scoring system performance is analyzed in terms of discrimination power, which means the ability of a rating system to determine the ex-ante cases of default and those of the repayment. Rating system with the maximum value for this criterion will be able to identify in advance all debtors who will not repay the loan. The approach used to quantify the discrimination power of a rating system is designated by the ROC curve and its index of content. ROC curve is a graphic expression of the relationship between the percentage of

[2] BPI – Bulletin of the insolvency proceedings , CIP-Head Office of event Payments , CRB –Risk Banking Head Office

bad taxpayers identified by model -*Hit Rate*- and *false alarm rate*[3]. ROC curve concavity reveals the extent to which the selected variables have a large power of discrimination, so the model as a whole is able to achieve a ranking of borrowers according to their probability of default (chart no. 1).

The model fails to focus the majority of cases of default in the riskiest categories (with the lowest score) when the ROC test curve tends to the sides of the square unit, in fact, the concavity of the ROC curve is the equivalent of scores with an informational content, being the decreasing function. A model that does not reveal the power of discrimination, is highlighted by the random spread on the graphic of default events, without a specific focus, so that the ROC curve would be similar to the first leap. Intuitive representation based on ROC curve is completed by the index or table of contents (AUROC), which expresses the area bounded by ROC curve. A reasonable model presents a summary of the ROC curve index of at least 75 %.

Chart no. 1: ROC curve



The robustness assessment of discrimination power of the scoring system is provided by completing the analysis based on ROC curve with econometric tests that are using the *logit* model, the purpose of the analysis being the same, namely to test the information relevance of the scores, provided by the *scoring* system at different levels of aggregation. From a functional viewpoint, the econometric tests are formulated as univaried analyses, underlying the usual regression statistics with binary dependent variable. Thus, the predictive ability of scores determined by the *scoring* system is considered in relation to the *McFadden* R2 statistic indicators. In the level of the financial score is inclusively checked the statistical relevance of each component indicator, the signification limit is considered to be the 20 percent value of the associated probability to the coefficient univaried estimation, simultaneously to a level of at least 1 percent of the statistical indicator R2 - *Mc Fadden*.

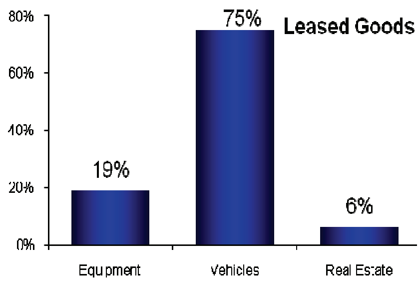
2. The structure of the financings sample used in the finance lease system to be tested and validated

The sample consists of 250 financings granted in leasing system. The analyzed NFI does not grant consumer credits or encumbrances. We considered the lease contracts concluded between 2008 and 2010, after the commencement of the financial crisis. Financings include equipment, cars and real estates. Financings are exclusively granted to legal entities. Most

[3] The highest level of accuracy (considering the explanations provided) can be reached by improving the alarm threshold level against the relative importance between prediction errors. These errors fall into two categories: unidentified non-payments (type 1 error) and false alarms (type 2 error). Type 1 error indicates the instance in which the model sends a debtor to 'payment' category only to discover in the near future that the debtor mentioned before can no longer pay the debts. Type 2 error indicates the instance in which the model sends a debtor to 'non-payment' category only to discover in the near future that the debtor mentioned paid all outstanding debts to NFI.

financings (from a numerical point of view) were granted for cars (chart no. 2), followed at a great distance by work equipment. Only 6% of the loans included in NFI's portfolio were granted for real estates.

Chart no. 2: The structure of the portfolio selected according to the type of the financed object

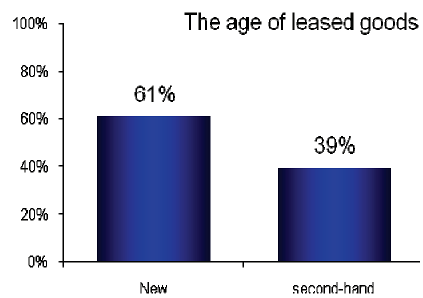


From the perspective of business sector distribution, the structural analysis suggests a cautious approach on NFI's side, the HHI index[4] slightly exceeding 1000 points (market average concentration level). Excepting non-food trading sector, all the other sectors represent no more than 10% of NFI's portfolio. Thus, the creditor manages to significantly reduce the exposure concentration risk for a certain field of activity.

Most of the clientele originates from trade, both food trade including restaurants, bars and the like and non-food trade (about 41 %), freelancers and management consultants (about 8%). The clientele originating from the construction sector represents 7% of the portfolio, while debtors from the transport or real estate brokerage sector represent 7%. The structural analysis of credit portfolio against the age of the funded goods indicates the prevalence of the new goods, while only 39% represent '*second-hand*' goods (chart no. 3).

During the period considered, 2008-2010, second-hand goods financing increased to the detriment of new goods and this is the reason why the level of second-hand goods is quite high. Based on the data in NFI's financing portfolio, we will attempt to test the discriminating power corresponding to the system used to evaluate credit applicants by using ex-post testing mechanism procedures.

Chart no. 3: The structure of the selected portfolio according to the age of financed goods



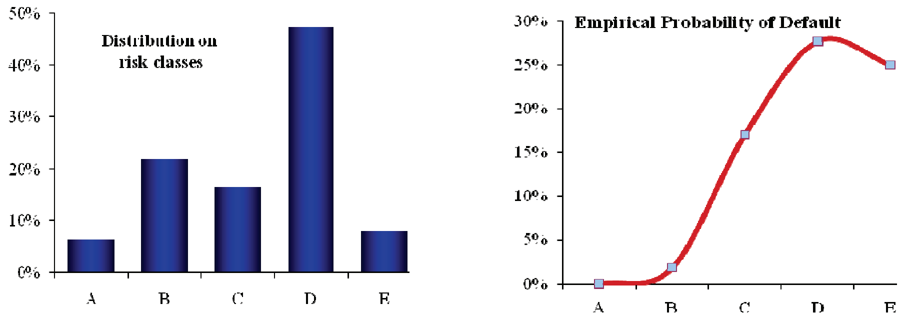
3. Testing of discriminating power corresponding to the *scoring* system designed

The objective of ex-post testing analysis is to appraise the extent to which the notation system criteria and final *scoring* are statistically important for the early identification of the

[7] Herfindahl-Hirschmann index (HHI) measures market concentration, namely the extent to which a small number of companies represents the largest share of the market.

non-payment instances associated with the loans granted by NFI. For the notation system, the discriminating power testing starts from the qualitative analysis of the notation scale. This is appraised by considering debtors distribution and the monotony of non-payment empiric probabilities recorded in risk classes (chart no. 4).

Chart no. 4: Risk class distribution and non-payment empirical probability corresponding to the analyzed portfolio



The graphical analysis indicates that more than a half of the portfolio comprises D- and E-category clients. This indicates an unjustified concentration of debtors in risky classes and this seriously challenges the capacity of the notation system to delimit ex-ante defaulters. Meanwhile, the non-payment empirical probability corresponding to 'E' risk class , significantly inferior to the one corresponding to 'D' risk class, clearly indicates the limited capacity of the notation system to classify debtors by risk. These results are confirmed by the filters used to test the similarity between the density functions corresponding to the two observation arrays: payment and non-payment. The solution we opted for was to overlap the histograms of the two debtor categories by considering their *scoring* on the date the financing decision was validated (chart no. 5).

Chart no. 5: *Scoring*-based debtors' classification

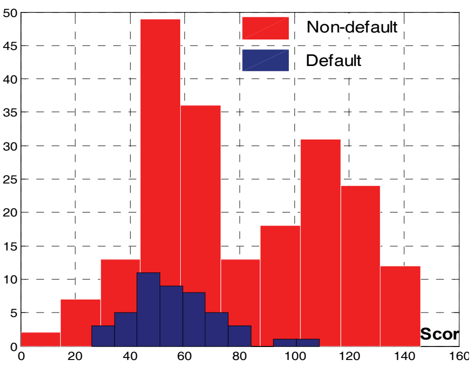
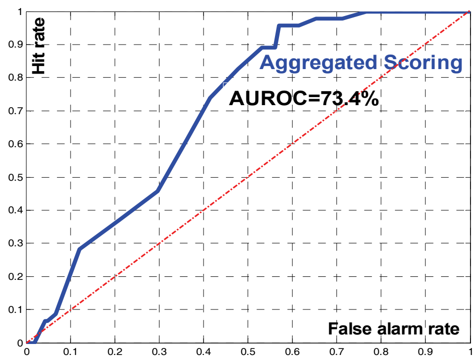
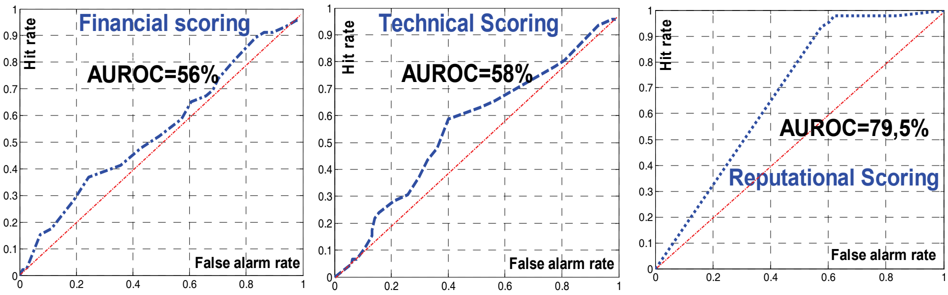


Chart no. 6: ROC curve (aggregated)



The test developed indicates that the defaulter's histogram partially overlaps the non-defaulters' histogram, from 30 to 90 points of the notation system. Moreover, there are a great number of non-defaulters recorded with *scoring* values inferior to the ones of the defaulters. Alert signs are also generated by the bimodal shape of non-defaulters distribution and the causes of such alerts must be thoroughly investigated both in relation with the discriminating power of the components that form NFI's aggregated rating and with NFI's business strategy. Using 'ROC' curve to test its discriminating power, we can clearly see the low informational level of the ratings generated by the notation system (chart no. 6) against the low performances corresponding to the financial *scoring* (chart no. 7).

Chart no. 7: ROC curve (on components)



The weak concavity of ROC curve corresponding to the financial *scoring* highlights the reduced discriminating power of the financial indicators used in the notation process that prevents an accurate organization to the debtors based on non-payment probability. Thus, financial *scoring* fails to concentrate the most non-payment cases in high-risk categories (lowest-*scoring*), while ROC test curve comes near the unit square diagonal. Technical *scoring* is also responsible for the low added value corresponding to credit applicants screening process. These conclusions are reinforced by econometric univariate tests (table no. 5).

Table no. 5: Estimates on the *logit* function

Score	Coefficient	Prob.	R2MF	Log likelihood
Financial Score	-0.01553	0.3071	0.004439	-119.0234
Technical Score	-0.01741	0.4371	0.002444	-119.2619
Reputational Score	*-0.04579*	*0.0001*	*0.114643*	*-105.8481*

Although the sign of the coefficients associated with each type of score, credit risk corresponds to the economic intuition, the credit risk is negatively correlated with the score on each component, and only in case of reputational score the intensity of the relationship with non-payment events is significantly different from zero. High probabilities of meeting the hypothesis that coefficients related to financial and technical scores are not different from zero and very low level of performance indicator R-square *McFadden*, suggests the need to review the methodology for building quantitative *scoring*.

4. Solutions on the Review's quantitative scoring

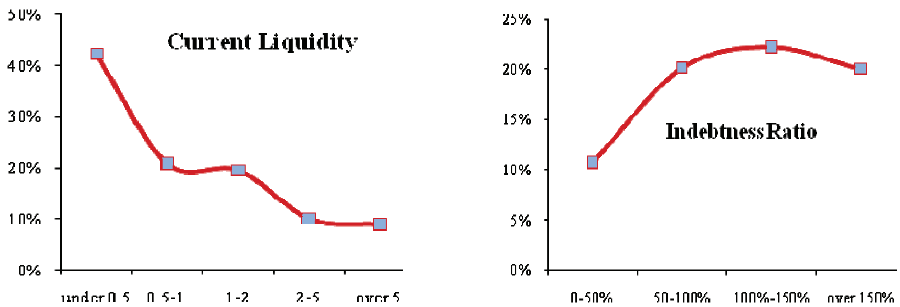
Reviewing the noting methodology of quantitative *scoring* performance covers both quantitative indicators eliminating irrelevant statistics in order to identify early default events, and how to aggregate the individual scores. Both processes are based on *logit* model.

Logit regression belongs to the set of conditional probabilities and is a direct method for estimating the default probability. Additional advantages that the *logit* model has relative to other discriminate analysis methods are: (a) shall not speculate on the distribution of exogenous variables, although its sensitivity is known for extreme values, (b) allows the analysis of the data set and under conditions of unequal masses between situations of default and repayment, (c) model coefficients can be interpreted separately, as the importance or the statistical significance of explanatory variables can be assessed (except the multicollinearity situations), (d) allows the inclusion of state variables in the analysis (such as loan type and legal status), but only after their prior coding.

Control is carried out based on empirical probability of default depending on the intervals value of each indicator. Intervals value showing similar levels of default probability default are merged. The score is awarded for the ratio between the highest repayment probability and that corresponding to the appropriate range. The aggregate modality of individual scores is given by estimated coefficients of multivariate *logit* regression. *Scoring* function is derived from the short list of indicators resulting from univariate analysis using progressive selection procedure.

In this study, among the financial indicators used by NFI's *scoring* system, only current liquidity and, partially, indebtedness ratio empirically confirm their statistic importance in anticipating non-payment instances, at the debtors level (chart no. 8).

Chart no. 8: Non-payment empirical probabilities in relation to current level of liquidity and indebtedness ratio



Data analysis indicates that about 45 % of the companies with a current liquidity level under 0.5 cannot pay their debts to NFI in the following year, while more than 90% of the companies with a current liquidity level over 2 will pay their debt (chart 8). About 20% of the companies with an current liquidity between 0,5 and 2 stop paying their debts within one year. About one-fifth from the companies with a high debt that exceeds 50% stop paying their debts within one year, while, legal debtors with an indebtedness ratio less than 50 percent have a default risk two times lower. Statistical relevance of the two indicators is confirmed by univariate analysis (table no. 6) conducted with score values (interval value).

Univariate test suggests a lack of information content of profitability indicators. Gross margin showed even in the sample analyzed a slightly positive influence on the occurrence of default events. The result on profitability indicators are not, however, a surprise, given the likely distorted presentation of image profitability in financial reports.

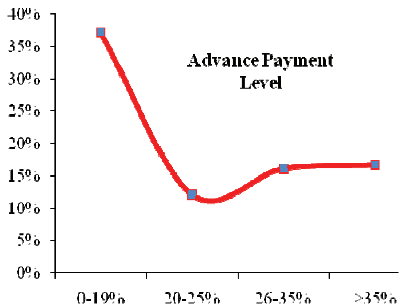
Table no. 6: Econometric results of univariate analysis with financial indicators

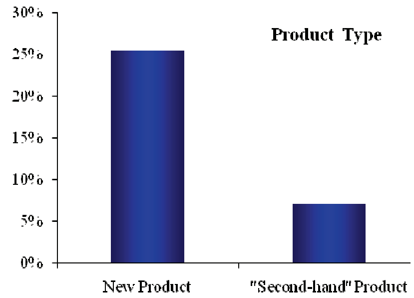
	Indicator	Coefficient	Prob.	R2MF	Log likelihood
1	Solvency rate	-0.00022	0.8655	0.000126	-119.5391
2	*Indebtedness ratio*	*0.765718*	*0.1011*	*0.012859*	*-118.0168*
3	*Current liquidity*	*-0.59017*	*0.0008*	*0.05433*	*-113.0588*
4	Gross margin	1.64E-05	0.954	0.008558	-118.531
5	ROA	-0.17572	0.5389	0.001693	-119.3517

Note: Financial indicators were transformed into state variables, classified into homogenous categories based on credit risk. Score awarded to each state is represented by the relative level of default probability to the high risk class. For Indicators debt service ratio and net cash data were not available.

Distinct from risk variables used to assess applicants for funding, we believe that NFI must optimize the use of funding provided the facility characteristics such as increasing the advance or the type of the financed property (chart no. 9).

Chart no. 9: Empirical default probabilities in relation to client's down payment and type of product





From analyzing these elements has been found that the default risk is very high (about 37 percent) for facilities where client input is less than 20 percent of the value of goods purchased, while the average probability of default for financing granted under an advance higher than 20 percent is 2.5 times lower. Empirical research of non-paying debtors profile was completed with information on usage of the asset acquired (new or in use). Univariate tests for these additional variables generated encouraging results in terms of discriminated analysis perspective (table no. 7).

Table no. 7: Econometric results of univariate analysis with complementary indicators

	Exogenous variable	Coefficient	Prob.	R2MF	Log likelihood
1	Advance	-0.7831	0.0014	0.0399	-114.7882
2	Product	0.5969	0.0006	0.0626	-112.0687

* Note: new products receive a score of 3.5 while second hand products are marked with 1

From univariate analysis conclusions, the effort to build an alternative mechanism for *scoring* on the quantitative component will focus on two financial indicators, namely the current liquidity and indebtedness rate, along with two variables that describe the technical risk, namely the product type and the level of contribution of applicant's own credit. Given the complexity of the phenomenon researched and the objective limits on the amount of information available, the multivariate selection procedure of the determinant factors followed the progressive approach. The first determinant factor introduced in the functional form of the model was the variable *product*, showing the highest discrimination power in univariate testing. Appearance is a distinguishing characteristic of credit risk profile of leasing, as highlights the financier's vulnerability of new goods towards a significant decrease of market price after the first use. Then followed the current liquidity and advance share, elements that enhance the performance of econometric *logit* regression (table no. 8).

Table no. 8: Estimation of multivariate *scoring* function

Variable	Coefficient	Std. Error	z-Statistic	Prob.
PRODUCT	0.468929	0.179785	2.608282	0.0091
CURRENT LIQUIDITY	-0.433524	0.186225	-2.327960	0.0199
ADVANCE RATE	-0.458200	0.261969	-1.749063	0.0803
C	-0.762416	0.920912	-0.827892	0.4077
Log likelihood	*-106.4466*	*Hannan-Quinn criter.*		*0.902662*
Restr. log likelihood	*-119.5541*	*Avg. log likelihood*		*-0.424090*
LR statistic (3 df)	*26.21505*	*McFadden R-squared*		*0.109637*

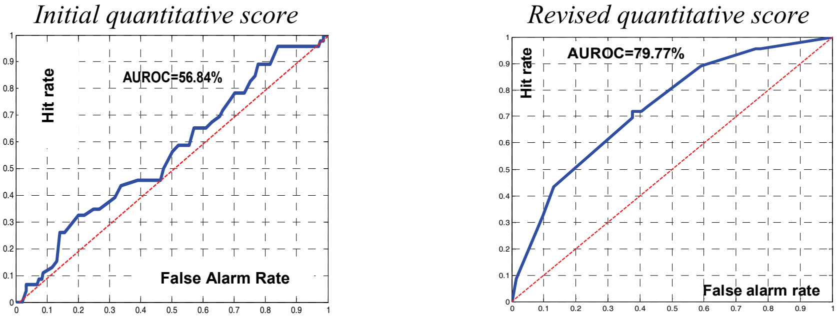
Note: The criteria used were transformed into state variables, classified into categories based on homogenous credit risks. Score awarded to each state is represented by the relative level of default probability towards the high risk class.

The introduction of variable degree of indebtedness in the functional form of the model does not provide added value in the identification process of default events, the associated coefficient being zero for a significance level of over 60 percent, while the R- *McFadden* squared performance indicator records only a slight increase.

Based on estimated *logit* function, were calculated the theoretical (statistical) default probabilities for each observation in part. These were subsequently used to test the discrimination power of the new *scoring* system (chart no. 10).

Chart no. 10: Performance of quantitative *scoring* system before and after revision

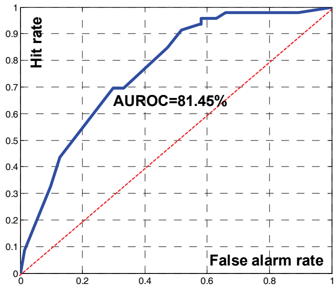
Initial quantitative score *Revised quantitative score*



The high value of content indicator ROC curve, significantly greater than the level of 75 percent, considered to be the referential in the field, indicates the reasonable accuracy of the forecast for the model's revised of quantitative *scoring*.

Combining the converted value on a scale of 100 points of the provided *scoring* by the *logit* model with the score provided by the noting system for the reputation in business, the aggregate score performance increased from 73.4 percent to a level of 81.45 percent in terms of index Contents of the ROC curve (chart no. 11). The aggregation of quantitative *scoring* with the reputational *scoring* follows the additive equiponderated procedure established at the NFI's analyzed level.

Chart no. 11: Aggregate discrimination power using the quantitative *scoring* system revised



Conclusions

Model validation and application of quantitative evaluation criteria for the discriminatory power revealed a number of vulnerabilities and areas for improvement in the NFI noting system. The weak link of this mechanism is represented by the quantitative *scoring*. While the power of discrimination related to the qualitative component (reputational *scoring*) meets the requirements of a good ex-ante identification of default cases, the power of discrimination for quantitative *scoring* is only marginally superior to a random model.

The review of the quantitative component for the *scoring* system was based on the individual performance evaluation of the financial indicators. Among these, only the current liquidity and the indebtedness ratio have passed the test of statistical relevance. Univariate testing revealed no information content of indicators of profitability, the result is not, however, a surprise, given the likely flawed presentation of profitability's image in interim financial reports and not audited ones.

Distinct from risk variables used to assess applicants for funding, we considered appropriate the capitalization of information related to the product's characteristics for the funding required, such as the type of asset financed. Appearance is a distinguishing characteristic of the credit risk profile in the leasing domain, as highlights the financier's vulnerability of new goods towards a significant decrease in market price after the first use. Univariate empirical analysis confirmed the statistical relevance of this criterion for modeling of default risk among clients of reviewed NFI.

Given the complexity of the phenomenon researched and the objective limits on the amount of information available, the selection procedure of multivariate determinants has followed the progressive approach. Non-paying debtor profile derived from multivariate econometric estimates has three predominant features: (a) follows the acquisition of new product, (b) shows an current liquidity below 50 percent, and (c) has an advance lower than 20 percent of the value of the property it wishes to acquire. For each of the three criteria have been created or reconfigured risk classes, based on value intervals, which were given new scores.

Aggregation of scores for each criterion is made using the derived functional form after *logit* regression estimation. The revised *scoring* mechanism allowed the significant increase of the discriminating power of the noting mechanism of NFI's clients.

Usage of *scoring* systems by NFIs in managing effectively the risks associated to granting finances can become a powerful tool of risk management only after their appropriate calibration at the specificity of the activities and financing products offered. Meanwhile, in the context of the current financial crisis, the use of such risk management techniques in NFIs level, can be preventively imposed by the supervisory authority namely the National Bank of Romania.

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